Sustainable Development Research; Vol. 7, No. 1; 2025
ISSN 2690-9898 E-ISSN 2690-9901
https://doi.org/10.30560/sdr.v7n1p136

Evaluation of the Policy Effects of Low-Carbon City Pilot Projects Based on the PSM-DID Model

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Received: February 20, 2025 Accepted: March 12, 2025 Online Published: March 23, 2025

Abstract

In the context of the dual-carbon policy, evaluating the implementation effects of low-carbon city pilot policies is of great significance. Based on panel data from 284 prefecture-level cities in China between 2004 and 2020, this paper integrates the Propensity Score Matching (PSM) method with the Difference-in-Differences (DID) method, referred to as the PSM-DID model. By employing parallel trend tests, placebo tests, robustness checks, and heterogeneity analyses, the implementation effects of the low-carbon city pilot policies are evaluated and compared with those from the traditional DID model. The results indicate that: (1) The low-carbon city pilot policies significantly curb carbon emissions in eastern China, while the effects in central and western regions are relatively weak; (2) Factors influencing carbon emissions differ significantly across regions. In particular, clean energy structure and per capita affluence have a greater impact on the eastern region, while the effect is weaker in the central and western regions; (3) The timing, scope, and regional factors of implementation significantly affect the policy outcomes. Policies implemented early yield more significant results than those implemented later, with regional development levels and scope of implementation playing key roles in shaping policy outcomes; (4) The PSM-DID model yields more reliable results than the DID model.

Keywords: carbon emissions, policy evaluation, PSM-DID, heterogeneity

1. Introduction

With the continuous increase in carbon emissions, the greenhouse effect, global warming, and rising sea levels have become increasingly prominent issues. In 2020, considering both domestic and international circumstances, China proposed at the United Nations General Assembly in September and in the subsequent "14th Five-Year Plan" that it would strive to achieve carbon peak by 2030 and carbon neutrality by 2060. This marked the transition of China's carbon emission reduction efforts from the exploration stage to the comprehensive promotion stage.

In July 2010, the National Development and Reform Commission issued the Notice on the Pilot Work of Low-carbon Provinces, Autonomous Regions, and Cities, officially launching the low-carbon pilot program. The first batch of pilot areas included five provinces, such as Guangdong and Liaoning, and eight cities, such as Tianjin and Chongqing. Since then, the second and third batches of low-carbon pilot areas were implemented in 2012 and 2017, further promoting the construction of low-carbon cities and regions. As a crucial measure for carbon emission reduction in China, the LLC has attracted widespread attention.

The PSM-DID model combines the Propensity Score Matching (PSM) and Differences-in-Differences (DID) models. In the application of this model, data matching is performed first, followed by the application of the difference-in-differences model to the matched data.

Abroad, the PSM-DID model is widely employed to assess carbon emission reduction policies. For example, a study using panel data from 31 Chinese provinces and cities (2000-2017) with the DID and PSM-DID methods evaluated the impact of carbon emission trading policies. It found that the policy alleviated haze pollution in pilot areas and surrounding regions (Yang et al., 2022) Another study showed that low-carbon city pilot policies reduced carbon emissions by lowering carbon intensity (Song et al., 2022). A study from 2006 to 2016 explored the emission reduction effects of low-carbon city pilots, highlighting the role of increased R&D investment, energy efficiency improvements, and reductions in high-carbon industries(Wang et al., 2023) Moreover, research using an enhanced PSM-DID model found that new urbanization policies significantly reduced carbon emissions in pilot cities with regional variation (Xu et al., 2024).

In China, the PSM-DID model has gained notable attention. For instance, a study from 2007 to 2019 examined carbon emission trading pilot policies using provincial panel data and revealed that the policies not only reduced carbon emissions but also lowered sulfur dioxide emissions (Ying et al., 2022). Similarly, a multi-period study covering 275 cities from 2005 to 2019 found that low-carbon city pilot policies successfully reduced emissions, though the effect weakened over time(Chengying & Jianping, 2022). The PSM-DID model has also been applied to evaluate the combined effects of pollution rights trading and carbon emission trading, showing that the combined policy had a stronger effect on sulfur dioxide reductions than individual policies (Siyu & Bing, 2023). Furthermore, a study from 2000 to 2019 explored the effects of clean energy demonstration provinces, finding that these policies reduced carbon emissions while promoting economic development(Yan-ping et al., 2024).

In addition to carbon reduction, low-carbon city pilot policies may generate co-benefits such as improved air quality and enhanced public health. These ancillary advantages not only align with sustainable development goals but also broaden the policy's appeal to interdisciplinary audiences, including environmental scientists and urban planners. By integrating these co-benefits into the evaluation framework, this study aims to provide a more holistic understanding of the policy's multifaceted impacts.

While the PSM-DID model has proven effective in evaluating emission reduction policies, many studies rely on provincial-level data, with fewer focusing on city-level data and regional variations. This paper uses panel data from 284 prefecture-level cities in China (2004-2020) to assess the impact of low-carbon city pilot policies, focusing on urban carbon emission reductions. To ensure model reliability, parallel trend, placebo, and robustness tests were conducted, and a heterogeneity analysis was performed based on policy batch, scope, and region. The results are compared with the traditional DID model, aiming to provide theoretical insights for future carbon emission reduction policy implementation.

2. Research Methods and Data Sources

2.1 The PSM-DID Model

2.1.1 Propensity Score Matching (PSM)

The basic principle of PSM is to replace multiple covariates with a single score to balance the distribution of covariates between the treatment and control groups. This method mimics randomization in non-randomized studies by addressing confounding factors, thereby reducing selection bias. In essence, PSM narrows the difference between the control and treatment groups. The main steps are as follows: estimating the propensity score, matching participants based on their propensity scores, and calculating the average treatment effect (ATT) for the treated participants. The formula for ATT is as follows:

$$ATT = E(Y_{1i} - Y_{0i}|treat_i = 1) = E[\, E(Y_{1i}|treat_i = 1, P(x_i)) - E(Y_{0i}|treat_i = 0, P(x_i)) \,|treat_i = 1\,] \tag{1}$$

Where, Y_{1i} and Y_{0i} respectively represent the carbon emissions of the same individual implementing the policy and those without implementing the policy, but here Y_{0i} cannot be directly observed, and $P(x_i)$ represents the conditional probability of implementing the policy for a sample given the sample characteristic x_i.

2.1.2 Differences-in-Differences Methods (DID)

The DID method is widely used to analyze the "treatment effect." In a typical application, using panel data, individuals are divided into two groups: the "treatment group," which is exposed to policy shocks, and the "control group," which is not influenced by the policy. The core idea of the DID method is to eliminate biases caused by unobserved fixed factors and external time effects by comparing the changes in the treatment and control groups before and after the treatment. The model for the DID method is as follows:

$$Y = \beta_0 + \beta_1 \times treat + \beta_2 \times year + \beta_3 \times treat \times year + \alpha \times Z + \varepsilon \tag{2}$$

Among them, the variable "*treat*" takes the value of 1 for cities where the policy is implemented and 0 for the rest. The variable "$year$" takes the value of 0 before the policy implementation and 1 after it. The interaction term "$treat \times year$" represents the treatment indicator for the policy. Z denotes the control variables that also affect the dependent variable. ε is the random disturbance term. The estimator of β_3 is the estimated coefficient of the standard DID model, representing the policy effect.

2.1.3 PSM-DID

The PSM-DID model combines Propensity Score Matching and Differences-in-Differences to improve the evaluation of policy interventions by addressing selection bias and unobserved heterogeneity.

In the first step, PSM is used to match treatment and control groups based on observable characteristics, ensuring that these groups are comparable at baseline. This reduces selection bias by aligning units with similar pre-treatment attributes. After matching, the DID approach is applied to the matched data, which compares the differences in outcomes before and after the policy intervention between the treated and control groups. This step helps estimate the causal effect of the policy.

While the traditional DID method assumes parallel trends between treatment and control groups (i.e., that they would have followed the same trajectory without the intervention), PSM-DID enhances robustness by addressing potential confounding factors through the matching process. By reducing bias in the selection of treatment and control units, PSM-DID provides more reliable estimates, especially when treatment assignment is non-random, such as in policy scenarios like low-carbon city pilot programs.

This hybrid approach is particularly beneficial when evaluating policies where random assignment is not possible and when the data includes both pre- and post-treatment periods, making it a powerful tool for policy impact evaluation.

The selection of low-carbon pilot cities may be non-random. For example, pilot cities may be prioritized due to advantages such as economic foundations, industrial structure, or policy implementation capacity, which can directly influence carbon emissions. To reduce selection bias, this study employs PSM based on observable characteristics (e.g., population size, industrial structure, energy structure) to match the treatment group (pilot cities) and the control group (non-pilot cities), ensuring a balanced distribution of characteristics before policy implementation. The DID method is then applied to the matched data to compare the pre- and post-policy intervention outcomes between the treatment and control groups. However, PSM cannot fully eliminate the influence of unobservable factors (e.g., local government's environmental priorities). Future studies could address this limitation using instrumental variables or natural experiment designs.

2.2 Data Sources and Variable Settings

2.2.1 Data Source

This paper evaluates the implementation effect of the LLC based on panel data from 284 prefecture-level cities in China, covering carbon emissions and influencing factors from 2004 to 2020. The empirical analysis primarily relies on data from the China Urban Statistical Yearbook, with missing values for individual indicators filled by interpolation. Consumption data for natural gas, liquefied petroleum gas, and electricity are also from the China Urban Statistical Yearbook, while the ratio of coal-fired power generation to total electricity generation is sourced from the China Electric Power Yearbook.

2.2.2 Variable Setting

1) Explained variable

The dependent variable is carbon emissions, denoted as lnC in logarithmic form in this chapter. Carbon emissions were calculated, with missing values interpolated. Specifically, the calculation of carbon dioxide emissions in this study follows the methods of Zhou Di (Di et al., 2019), Han Feng (Feng & Rui, 2017), and other scholars. The calculation formula is as follows:

$$C = C_n + C_p + C_e = k \times E_n + \gamma \times E_p + \varphi \times (\eta \times E_e) \quad (3)$$

Where C represents urban carbon emissions, C_n, C_p, and C_e are the carbon emissions from the consumption of natural gas, liquefied petroleum gas, and electricity, respectively. E_n, E_p, and E_e are the consumption levels of natural gas, liquefied petroleum gas, and electricity. k and γ are the carbon emission coefficients for natural gas and liquefied petroleum gas, respectively. φ is the greenhouse gas emission coefficient for the coal power fuel chain, equivalent to *1.3203 kg/(kW·h)* of carbon dioxide, and η is the ratio of coal-fired power generation to total power generation.

2) Pilot state variable

The status variable for the low-carbon pilot policy is LLC, where the value is 1 for cities in the year the policy is implemented and thereafter, and 0 for other years.

3) Control variable

The control variables include population size, per capita affluence, industrial structure, energy consumption intensity, energy structure, output value ratio, average employee salary, greening rate of built-up areas, financial deepening, fiscal expenditure intensity, R&D investment, and the energy structure (power ratio), as shown in Table 1.

Table 1. Symbols and descriptions of control variables

symbol	Variable name	Description
P	Population size	The total population of each prefecture-level city at the end of the year
ED	Per capita affluence	Measured by the ratio of GDP to the total population of each prefecture-level city at the end of the year
IS	Industrial structure	The ratio of the added value of the secondary industry to the gross product of each prefecture-level city
EI	Energy consumption intensity	The ratio of energy consumption to the added value of the secondary industry in each prefecture-level city
ES	Energy structure	The ratio of carbon dioxide emissions to energy consumption in each prefecture-level city
IS2	Output value ratio	The ratio of the output value of the tertiary industry to the secondary industry in each prefecture-level city
lnWAGE	Average employee salary	Average wages of employees, expressed in logarithmic form
GRE	Greening rate of built-up areas	The ratio of the green coverage area to the built-up area in the urban built-up area
lnFINA	Financial deepening	Represented by the ratio of the loan balance of financial institutions to GDP, expressed in logarithmic form
FISCAL	Fiscal expenditure intensity	The ratio of local fiscal expenditure to GDP
RD	R&D investment	The ratio of scientific research expenditure to total financial expenditure
FS	Energy structure (power ratio)	The ratio of electricity consumption to total energy consumption

3. Empirical Analysis

In July 2010, the National Development and Reform Commission issued the Notice on the Pilot Work for Low-carbon Provinces, Regions, and Cities. This notice identified the first batch of pilot projects in Guangdong, Liaoning, and cities such as Tianjin and Shenzhen. The second batch of pilot projects, launched in 2012, expanded to Beijing, Shanghai, and Hainan Province. The third batch, in 2017, included cities such as Wuhai, Shenyang, and Dalian.

The LLC indicates the implementation of the LLC, with a value of 1 for the years following its introduction in prefecture-level cities, and 0 for other years. The chart below shows, by batch, the regions where the policy was applied.

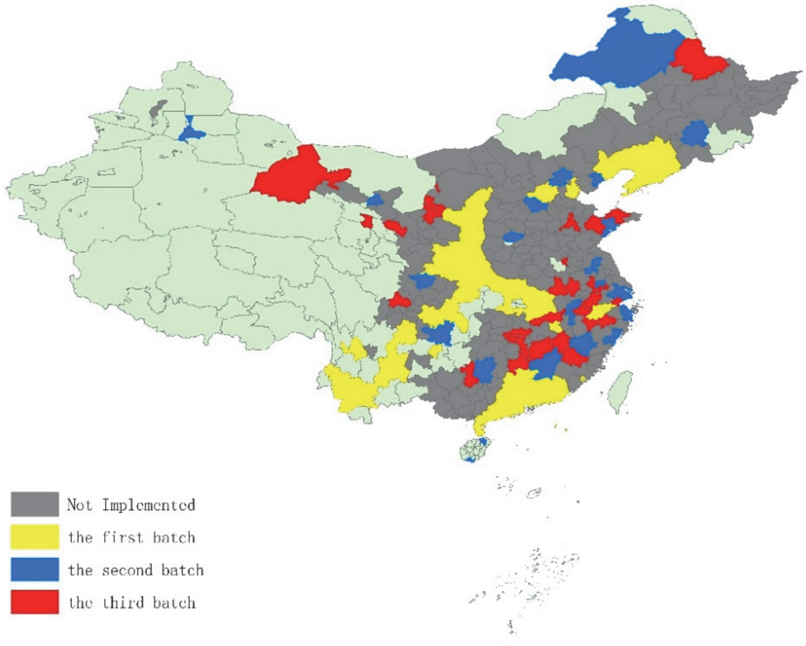

Figure 1. Map of Low-Carbon City Pilot Policy Implementation Locations

All non-white areas in Figure 1 represent the 284 prefecture-level cities analyzed in this study. The yellow area indicates the first batch of prefecture-level cities that implemented the LLC (low-carbon city pilot policy) in 2010, including 72 cities such as Tianjin, Chongqing, and those in Guangdong. The blue area represents the second batch, which began the policy implementation in 2012. This batch includes 24 cities, such as Beijing, Shanghai, and some in Hainan. The red area shows the third batch, where the policy was implemented in 2017, covering 30 cities, including Wuhai, Heihe, and Nanjing. The specific list of these implementation locations is as follows:

Table 2. Summary of Low-Carbon City Pilot Policy Implementation Locations

Batch	List of prefecture-level cities
Batch 1 (2010)	Dongguan, Zhongshan, Lincang, Dandong, Lijiang, Yunfu, Foshan, Baoding, Baoshan, Shiyan, Nanchang, Xiamen, Xianning, Xianyang, Shangluo, Dalian, Tianjin, Xiaogan, Ankang, Yibin, Baoji, Guangzhou, Yan 'an, Huizhou, Fushun, Jieyang, Kunming, Zhaotong, Pu 'er, Qujing, Chaoyang, Benxi, Hangzhou, Meizhou, Yulin, Wuhan, Hanzhong, Shantou, Shanwei, Jiangmen, Shenyang, Heyuan, Shenzhen, Qingyuan, Weinan, Zhanjiang, Chaozhou, Yuxi, Zhuhai, Panjin, Zhaoqing, Maoming, Jingzhou, Jingmen, Yingkou, Huludao, Xiangyang, Xi 'an, Guiyang, Liaoyang, Ezhou, Chongqing, Tieling, Tongchuan, Jinzhou, Fuxin, Yangjiang, Suizhou, Anshan, Shaoguan, Huanggang, Huangshi
Batch 2 (2012)	Sanya, Shanghai, Urumqi, Beijing, Nanping, Jilin, Hulunbuir, Ningbo, Guangyuan, Jincheng, Jingdezhen, Guilin, Chizhou, Haikou, Huai 'an, Wenzhou, Shijiazhuang, Qinhuangdao, Suzhou, Ganzhou, Zunyi, Jinchang, Zhenjiang, Qingdao
Batch 3 (2017)	Sanming, Wuhai, Jiujiang, Lu 'an, Lanzhou, Nanjing, Hefei, Ji 'an, Wuzhong, Jiaxing, Xuancheng, Changzhou, Chengdu, Fuzhou, Liuzhou, Zhuzhou, Jinan, Huaibei, Xiangtan, Weifang, Yantai, Quzhou, Xining, Chenzhou, Jiuquan, Jinhua, Yinchuan, Changsha, Huangshan, Heihe

Note. Figures in brackets indicate the year the policy was implemented

To avoid interference from the carbon emission trading pilot in the evaluation results, cities with dual pilot policies listed in Table 3 were excluded from the panel data of 284 prefecture-level cities in this section. The remaining data were used for empirical analysis in this study. Among them, prefecture-level cities with low-carbon city pilot policies formed the treatment group, while those without these policies served as the control group. The following is a list of prefecture-level cities that implemented both the carbon emission trading pilot and the LLC.

Table 3. Summary of Locations Implementing Dual Pilot Policies

Batch	List of prefecture-level cities
Batch 1 (2013)	Shanghai, Dongguan, Zhongshan, Yunfu, Foshan, Beijing, Tianjin, Guangzhou, Huizhou, Jieyang, Meizhou, Shantou, Shanwei, Jiangmen, Heyuan, Shenzhen, Qingyuan, Zhanjiang, Chaozhou, Zhuhai, Zhaoqing, Maoming, Yangjiang, Shaoguan
Batch 2 (2014)	Shiyan, Xianning, Xiaogan, Wuhan, Jingzhou, Jingmen, Xiangyang, Ezhou, Chongqing, Suizhou, Huanggang, Huangshi
Batch 3 (2016)	Nanping, Xiamen
Batch 4 (2017)	Sanming

Note. Figures in brackets indicate the year the policy was implemented

3.1 Parallel Trend Test

Before constructing the PSM-DID and DID models, prefecture-level cities in both the treatment and control groups were required to exhibit no significant differences prior to the policy implementation. This section validates this assumption using parallel trend tests.

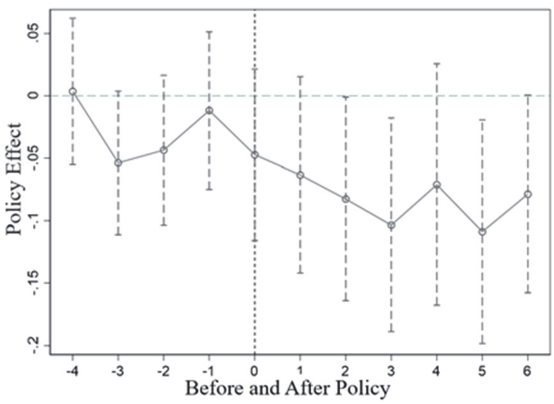

Figure 2. Parallel Trend Test for the DID Model

In the horizontal axis of Figure 2, -1 represents the year before the implementation of the LLC, 0 represents the year of policy implementation, and 1 represents the year following the policy implementation. As shown in the figure, prior to the policy's implementation, the dashed line representing the policy effect fluctuated around the baseline (policy effect = 0), with the absolute values of the policy effect remaining below 0.1, indicating no significant difference between the treatment and control groups. In the year of implementation and the three subsequent years, the policy effect continued to decline, remaining below -0.1, suggesting that the policy had an inhibitory effect on carbon emissions, thereby satisfying the parallel trend test requirements.

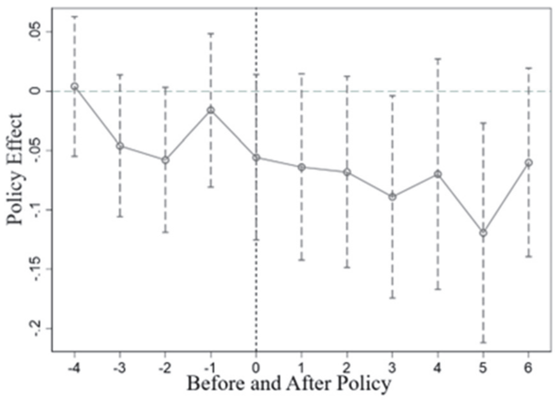

Figure 3. Parallel Trend Test for the PSM-DID Model

As shown in Figure 3, in the years prior to the implementation of the LLC, the dashed line representing the policy effect fluctuated around the baseline (policy effect = 0), with the absolute values of the policy effect consistently below 0.1, indicating no significant difference between the treatment and control groups. During the year of implementation and the following three years, the policy effect continued to decline. In the fourth year after implementation, the policy effect value slightly recovered, though the change was small. In the fifth year after implementation, the policy effect value dropped sharply, falling below -0.1, indicating that the policy had an inhibitory effect on carbon emissions and met the requirements of the parallel trend test.

To more accurately assess whether the data used in this paper meets the requirements of the parallel trend test, Table 4 is provided:

Table 4. Results of the Parallel Trend Test for the Policy Effect

Variable	DID	PSM-DID
LLC-4	0.0035	0.0041
	(0.12)	(0.14)
LLC-3	-0.0538*	-0.0460
	(-1.84)	(-1.51)
LLC-2	-0.0436	-0.0579*
	(-1.42)	(-1.86)
LLC-1	-0.0118	-0.0161
	(-0.37)	(-0.49)
LLC-0	-0.0473	-0.0557
	(-1.35)	(-1.57)
LLC+1	-0.0634	-0.0639
	(-1.58)	(-1.59)
LLC+2	-0.0826**	-0.0681*
	(-1.98)	(-1.66)
LLC+3	-0.1035**	-0.0890**
	(-2.37)	(-2.05)
LLC+4	-0.0711	-0.0698
	(-1.44)	(-1.41)
LLC+5	-0.1088**	-0.1194**
	(-2.39)	(-2.53)

LLC+6	-0.0786*	-0.0600
	(-1.95)	(-1.48)
Control variable	YES	YES
Urban fixed effect	YES	YES
Time-fixed effect	YES	YES
Observed value	4,063	3,723
R^2	0.9375	0.9381

The value of LLC-1 for cities in the treatment group in the year before the policy implementation is 1, while for other cities, it is 0. The value of LLC-0 in the year of policy implementation is 1, with other cities having a value of 0. One year after the policy implementation, the value of LLC+1 for cities in the treatment group is 1, while for other cities, it is 0. As shown in Table 4, most of the coefficients from LLC-4 to LLC-1 are not significant, while the coefficients from LLC+2 to LLC+6 are negative and mostly significant, indicating that the parallel trend test for the LLC generally meets the requirements.

3.2 Propensity Score Matching and Its Testing

The PSM-DID model combines PSM and DID model, so the PSM model must be applied before the DID model. Since the PSM model is suitable for cross-sectional data, two common matching methods are typically used. The first method involves converting the entire panel data into cross-sectional data for matching. However, it has been pointed out that this method may lead to the issue of "self-matching," which occurs when samples from different time periods are matched, leading to significant time trend effects in the final results (Shenxiang et al., 2021). The second method is phase-by-phase matching, where the panel data is divided into cross-sectional data for each year, and propensity score matching is performed on the data for each year. The matched cross-sectional data are then combined to form new panel data. Many scholars prefer the phase-by-phase matching method to avoid the "self-matching" issue (Böckerman & Ilmakunnas, 2009; Qilin & Jiayun, 2014). Therefore, this study adopts the phase-by-phase matching method. Since the panel data in this study spans from 2004 to 2020, only the matching results for selected years are presented.

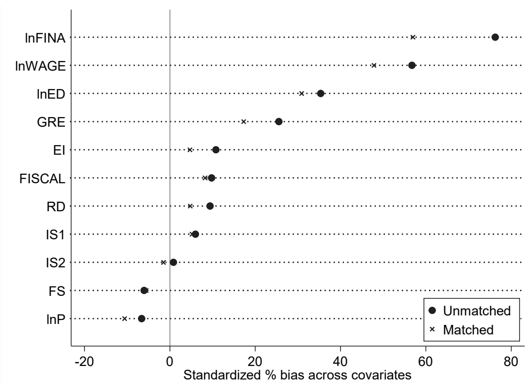

Figure 4. Matching Results of 2004 Low Carbon City Pilot Policy

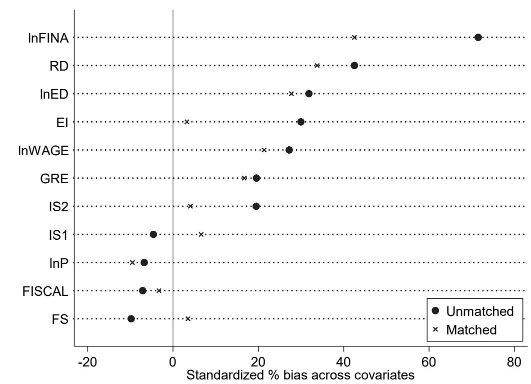

Figure 5. Matching Results of 2008 Low Carbon City Pilot Policy

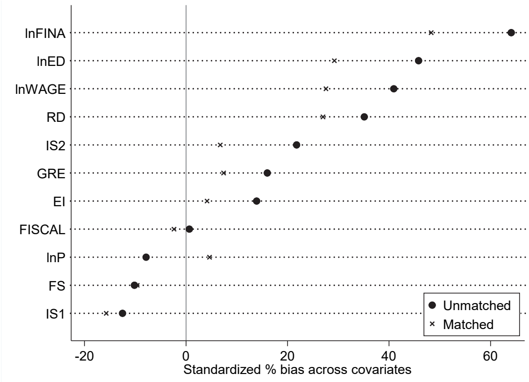

Figure 6. Matching Results of 2012 Low Carbon City Pilot Policy

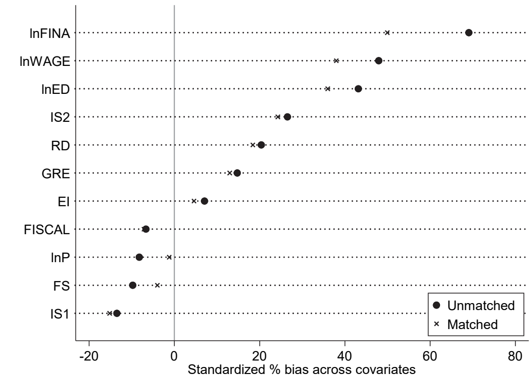

Figure 7. Matching Results of 2016 Low Carbon City Pilot Policy

The dots in Figures 4 to 7 represent the untreated data, while the crosses represent the processed data. After processing, most of the data points are closer to the straight line, indicating a better matching effect, a reduction in the difference between the treatment and control groups, and an improvement in the similarity between the two groups. The figure reflects the matching effect of the annual cross-sectional data but does not capture the overall matching situation. To illustrate the overall matching effect, the changes in kernel density before and after matching are shown(Qi & Jiaqi, 2024), providing a clearer view of the overall matching effect.

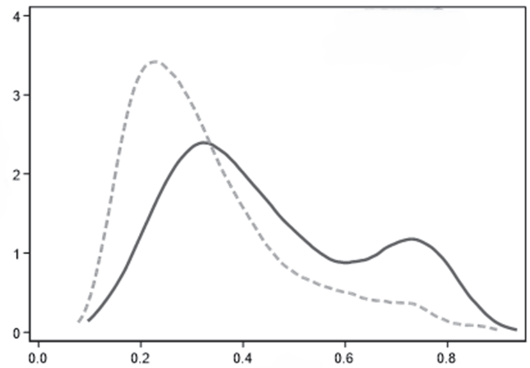

Figure 8. Matched Kernel Density Plots of the Pre-Treatment and Control Groups

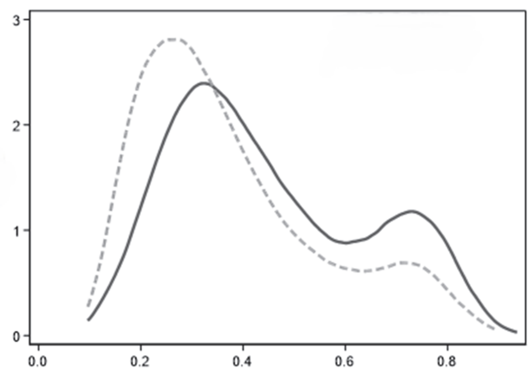

Figure 9. Matched Kernel Density Plots of the Post-Treatment and Control Groups

Figures 8 and 9 show the kernel density plots before and after matching; the dashed line represents the control group data, and the solid line represents the treatment group data. In Figure 8, the kernel density of the control group is higher than in Figure 9, and the difference between the dashed and solid lines before matching is larger than after matching, indicating that the propensity score matching effectively reduces the difference between the control and treatment groups, showing a good matching effect.

The following figure displays the data structure after matching, illustrating the data that meet the common support assumption and the data that do not, for both the control and treatment groups:

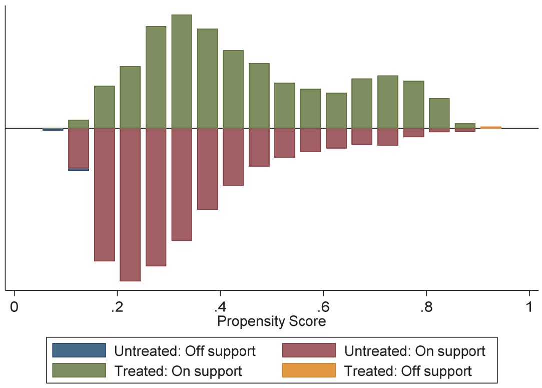

Figure 10. Data Structure After Matching

In Figure 10, blue represents the control group data that does not meet the common support assumption, red represents the control group data that does, green represents the treatment group data that does, and orange represents the treatment group data that does not meet the common support assumption. From the figure, it is evident that the majority of data in both the control and treatment groups meet the common support assumption, while only a small portion do not. Therefore, the double difference analysis can be performed on the matched data in this study.

3.3 The PSM-DID Model

The PSM model has already been completed, and an analysis of the matched data revealed that the DID model can be conducted. The following table presents the parameter estimation results of the PSM-DID and DID models.

Table 5. Parameter Estimation Results for the DID and PSM-DID Models

Variables	DID model	PSM-DID model
LLC	-0.0608*** (-2.96)	-0.0528** (-2.57)
lnP	0.9706*** (9.38)	1.0186*** (9.38)
lnED	0.7191*** (11.45)	0.7698*** (11.76)
IS1	0.7031*** (4.09)	0.5580*** (2.79)
EI	0.0001*** (6.67)	0.0001*** (6.15)
IS2	-0.0480*** (-4.08)	-0.0585*** (-2.80)
lnWAGE	0.1332** (2.36)	0.1648** (2.41)
GRE	0.2969*** (3.27)	0.3514*** (3.61)
lnFINA	0.0884** (2.45)	0.1159** (2.53)
FISCAL	0.3556*** (3.25)	0.4576** (2.50)
RD	-0.8048	-0.4850

	(-1.29)	(-0.73)
FS	1.4204***	1.4274***
	(13.63)	(12.99)
Cons	-7.9741***	-8.5905***
	(-9.61)	(-9.26)
Urban fixed effect	YES	YES
Time-fixed effect	YES	YES
Observed value	4063	3723
R^2	0.9373	0.9380

The parameter estimation results of the DID and PSM-DID models in Table 5 show that the LLC has a restraining effect on carbon emissions, confirming the policy's effectiveness in emission reduction. Among the control variables, the output value ratio and R&D investment reduce carbon emissions, while other control variables increase carbon emissions. The inhibitory effect of R&D investment is the strongest, indicating that higher R&D investment leads to faster development of green technology and a stronger reduction in carbon emissions. By using propensity score matching, the PSM-DID model better controls for baseline characteristic differences than the DID model, thus minimizing potential confounding effects from intervention selection bias.

3.4 Placebo Test

Since the selection of the policy implementation location is non-random, DID results may be biased. To eliminate potential bias caused by the choice of policy implementation site, a placebo test is conducted(Yijun et al., 2023). In this study, 87 cities are randomly selected as the virtual treatment group, and the remaining 152 cities are used as the virtual control group, with 400 sampling repetitions. These data are then applied to DID. Figures 11 and 12 show the placebo test results for the DID and PSM-DID models, respectively:

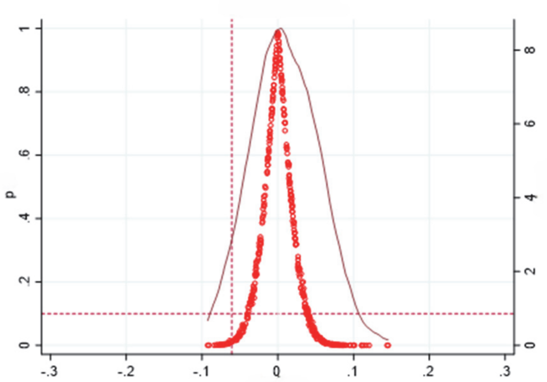

Figure 11. Placebo test results for the DID model

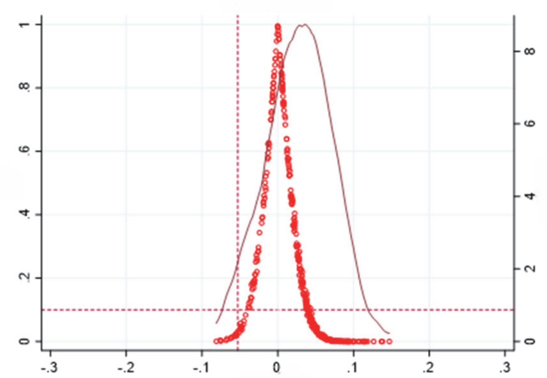

Figure 12. Placebo test results for the PSM-DID model

Figures 11 and 12 show the placebo test results for the DID and PSM-DID models, respectively. It can be observed that the p-values of the coefficients for the state variables of most virtual policy pilots are greater than 0.1, and the coefficients of the state variables for most virtual policy pilots are higher than those for the LLC variables. This suggests that the non-random selection of the LLC implementation site does not lead to any bias in the results.

Additionally, there are various methods for conducting placebo tests. The following method, based on the practice of Lin Yifu, conducts placebo tests one year prior to and two years after the policy implementation(LIN et al., 2020). Table 6 presents the parameter estimation results for the DID and PSM-DID models using this method:

Table 6. Placebo test results for prior policy implementation times

Variables	DID model		PSM-DID model	
	A year ahead	Two years ahead	A year ahead	Two years ahead
LLC_1	0.0505		-0.0307	
	(-1.24)		(-0.57)	
LLC_2		-0.0522		-0.0517
		(-1.31)		(-1.32)
Control variable	YES	YES	YES	YES
Cons	-7.9161***	-7.9295***	-8.4286***	-8.4340***
	(-5.53)	(-5.54)	(-5.43)	(-5.43)
Urban fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
Observed value	4063	4063	3723	3723

Note. *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively. The values in parentheses are t-values.

As shown in Table 6, the coefficients of the virtual low-carbon city pilot state variables do not pass the significance test when the policy implementation time is advanced by one year and two years, suggesting that the established model is robust.

3.5 Robustness Test

After establishing the DID and PSM-DID models, robustness tests were performed. Based on previous studies, we adjusted the data range before regression to prevent the models from being constrained by fixed data (JU et al., 2020; Weibing & Kaixia, 2019; Yi et al., 2017). Table 7 presents the parameter estimation results for both models.

Table 7. Robustness test results

Variables	DID model			PSM-DID model		
	Removing megacities	Winsorize at 1% level	Winsorize at 5% level	Removing megacities	Winsorize at 1% level	Winsorize at 5% level
LLC	-0.0607***	-0.0602***	-0.0775***	-0.0528**	-0.0508***	-0.0625***
	(-2.96)	(-3.39)	(-4.80)	(-2.57)	(-2.90)	(-3.93)
Control variable	YES	YES	YES	YES	YES	YES
Cons	-7.9741***	-8.6704***	-8.7168***	-8.5905***	-9.6940***	-9.0004***
	(-9.61)	(-12.67)	(-12.11)	(-9.26)	(-13.73)	(-11.87)
Urban fixed effect	YES	YES	YES	YES	YES	YES

Time-fixed effect	YES	YES	YES	YES	YES	YES
Observed value	4063	4063	4063	3723	3723	3723
R^2	0.9374	0.9541	0.957	0.938	0.9567	0.9594

Note. *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively. The values in parentheses are t-values.

In Table 7, the first and fourth columns display the parameter estimation results of the DID and PSM-DID models after removing mega-cities. The coefficients of the pilot state variables for the LLC are significant at the 1% level in all cases. The data in the second and third columns, and the fifth and sixth columns, represent the estimation results of the DID and PSM-DID models after 1% and 5% tail processing, respectively. The coefficients for the pilot state variables remain significant at the 1% level, and the regression results are not affected by changes in the data range. This indicates that the DID model established in the previous section is robust compared to the PSM-DID model.

3.6 Heterogeneity Analysis by Batches

The LLC are implemented in three batches, starting in 2010, 2012, and 2017, respectively. To explore whether the effects of LLC on carbon emissions differ across batches, this paper combines the data of different batches of treatment groups with the control group data for regression analysis. The regression results are shown in Table 8.

Table 8. The results were tested by batch heterogeneity analysis

Variables	DID model			PSM-DID model		
	Batch 1	Batch 2	Batch 3	Batch 1	Batch 2	Batch 3
LLC	-0.1018***	0.0049	-0.0563	-0.0892***	-0.0059	-0.0298
	(-3.59)	(0.16)	(-1.35)	(-3.07)	(-0.20)	(-0.70)
Control variable	YES	YES	YES	YES	YES	YES
Cons	-9.0008***	-8.2894***	-7.7919***	-9.6711***	-8.8909***	-8.3573***
	(-9.68)	(-8.95)	(-8.77)	(-9.07)	(-8.65)	(-8.20)
Urban fixed effect	YES	YES	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES	YES	YES
Observed value	3213	2941	3077	2900	2640	2767
R^2	0.9317	0.9339	0.9343	0.9321	0.9354	0.9348

Note. *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively. The values in parentheses are t-values.

As shown in Table 8, the coefficients of the LLC for the first batch of LLC in both the DID and PSM-DID models are negative and statistically significant, indicating that the first batch of LLC has an inhibitory effect on carbon emissions. In both the DID and PSM-DID models, the coefficients of the LLC for the second and third batches of LLC fail to pass the significance test, suggesting that these LLC have a minimal effect on carbon emissions. However, since the third batch was implemented in 2017 and the data in this paper only cover up to 2020, the relatively short period may have prevented the full policy effect from being observed.

3.7 Heterogeneity Analysis of The Scope of Policy Implementation

the LLC are implemented at both provincial and city levels. To explore where these policies are more effective, this paper follows the approach of Cao Qingfeng (Qing-feng, 2020) and conducts heterogeneity tests on the policy implementation scope. The results are presented in Table 9.

Table 9. Heterogeneity test of policy implementation scope

Variables	DID model		PSM-DID model	
	Implemented across the entire province	Implemented in a single city	Implemented across the entire province	Implemented in a single city
LLC	-0.0828***	-0.0246	-0.0744***	-0.0148
	(-2.96)	(-0.97)	(-2.61)	(-0.59)
lnP	1.1189***	0.8939***	1.1517***	0.9535***
	(9.37)	(8.24)	(9.02)	(8.28)
lnED	0.8252***	0.6289***	0.8481***	0.6628***
	(11.58)	(8.40)	(11.45)	(7.96)
IS1	0.5600***	1.0458***	0.4842**	1.0080***
	(2.65)	(5.48)	(2.12)	(4.67)
EI	0.0001***	0.0001***	0.0001***	0.0001***
	(5.20)	(7.53)	(5.03)	(6.68)
IS2	-0.0603***	-0.0361***	-0.0623***	-0.0320
	(-2.78)	(-2.65)	(-2.83)	(-1.37)
lnWAGE	0.1395**	0.1046**	0.1757**	0.1305**
	(2.30)	(2.06)	(2.32)	(2.10)
GRE	0.2045*	0.1690*	0.3151***	0.1926*
	(1.91)	(1.82)	(2.65)	(1.96)
lnFINA	0.0886**	0.1370***	0.1136**	0.1832***
	(2.23)	(3.45)	(2.19)	(3.56)
FISCAL	0.4357***	0.2357**	0.3763*	0.4368**
	(4.09)	(1.97)	(1.81)	(2.06)
RD	-1.5166**	-0.1525	-1.5230*	0.3924
	(-1.97)	(-0.24)	(-1.88)	(0.57)
FS	1.4975***	1.5202***	1.4987***	1.5422***
	(12.49)	(14.93)	(11.91)	(14.04)
Cons	-9.0143***	-7.3415***	-9.5687***	-8.0326***
	(-9.63)	(-8.72)	(-8.94)	(-8.53)
Urban fixed effect	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES
Observed value	3230	3468	2926	3140
R^2	0.9303	0.9384	0.9311	0.9391

Note. *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively. The values in parentheses are t-values.

Table 9 presents the results of the heterogeneity test on the implementation scope of the LLC under the DID and PSM-DID models. When the LLC is implemented at the provincial level, the coefficients of the pilot state variables in both the DID and PSM-DID models are negative and pass the 1% significance level test. When the policy is implemented at the city level, the coefficients of the pilot state variable in both models fail the significance test, indicating that the policy has a better effect when implemented at the provincial level and significantly inhibits carbon emissions. In the control variables of both models, the coefficients for population size and clean energy structure pass the significance test and are relatively large, suggesting that under the policy implementation, these factors play a greater role in promoting carbon emissions. The coefficient for scientific research investment passes the significance test, and its absolute value is relatively large, indicating that under the policy implementation, scientific research investment has a significant inhibitory effect on carbon emissions.

3.8 Regional Heterogeneity Analysis

The cities implementing the LLC are widely distributed, and the policy's impact on carbon emissions varies due to differences in geographic location, economic development, and population size. Following the approach of Wang Qiao and Yu Shuo (Qiao & Shuo, 2020), this paper examines the policy's effects across different economic regions, divided into three major zones. The results are presented in Table 10.

Table 10. Regional Heterogeneity Test Results

Variables	Eastern Region		Central Region		Western Region	
	DID	PSM-DID	DID	PSM-DID	DID	PSM-DID
LLC	-0.1443***	-0.1197***	-0.0014	0	-0.0357	-0.0231
	(-4.79)	(-4.21)	(-0.03)	(-0.00)	(-0.82)	(-0.52)
lnP	1.3150***	1.3916***	0.8811***	0.9338***	1.5281***	1.5069***
	-4.41	-4.48	-6.36	-6.71	-5.96	-5.43
lnED	0.6582***	0.6616***	0.7466***	0.8108***	0.8486***	0.8893***
	-7.04	-8.09	-5.8	-5.91	-6.08	-5.66
IS1	0.0729	-0.1964	1.3328***	1.1849***	0.6167	0.7845
	-0.25	(-0.64)	-4.82	-3.34	-1.44	-1.54
EI	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	-3.03	-3.06	-2.74	-2.62	-7.49	-6.56
IS2	-0.0732**	-0.0831***	-0.0447*	-0.062	-0.0655	-0.0161
	(-2.46)	(-2.66)	(-1.69)	(-0.86)	(-1.10)	(-0.16)
lnWAGE	0.2666	0.5626***	0.1045	0.0969	0.0992	0.1169*
	-1.52	-4.21	-1.35	-1.22	-1.48	-1.84
GRE	-0.0652	-0.0611	0.2976**	0.3673**	0.5913***	0.7920***
	(-0.46)	(-0.38)	-2.24	-2.58	-3.19	-3.97
lnFINA	0.0549	0.0566	0.1229**	0.2011**	0.1045	0.0819
	-1.04	-0.91	-2.24	-2.47	-1.38	-0.87
FISCAL	0.3322	0.8483	0.2834	0.4055	0.4219***	0.4664
	-1.26	-1.41	-0.84	-1.05	-2.95	-1.63
RD	1.647	3.2768**	-0.4317	-0.6022	-6.8353**	-5.8506*
	-1.4	-2.49	(-0.46)	(-0.61)	(-1.99)	(-1.82)
FS	0.9175***	1.1425***	1.9528***	1.9362***	1.2831***	1.3015***
	-5.51	-6.46	-11.5	-11.33	-8.66	-8.79
Cons	-10.3948***	-14.1266***	-8.0323***	-8.2207***	-10.7183***	-11.0530***
	(-5.18)	(-7.36)	(-7.16)	(-7.35)	(-6.62)	(-6.48)
Urban fixed effect	YES	YES	YES	YES	YES	YES
Time-fixed effect	YES	YES	YES	YES	YES	YES
Observed value	1377	1296	1649	1464	1037	963
R^2	0.9441	0.9443	0.9318	0.9316	0.9281	0.9289

Note. *, **, and *** denote the significance levels of 10%, 5%, and 1% respectively. The values in parentheses are t-values.

As shown in Table 10, the coefficient for the pilot state variable of the low-carbon city pilot policy in the eastern region is negative and passes the significance test, indicating that the policy has a significant positive effect, effectively reducing carbon emissions in this region. The coefficients for clean energy structure and per capita wealth are large, and the significance test reveals that the transition to clean energy and economic development are the primary drivers of carbon reduction in the region. Therefore, it is recommended that eastern cities further leverage their existing advantages through market-based carbon trading mechanisms and residential distributed energy subsidies.

In contrast, the coefficient for the pilot state variable of the low-carbon city pilot policy in the central and western regions does not pass the significance test, indicating that the policy's impact is weaker and less pronounced in these areas. This suggests that infrastructure investment and industrial decarbonization efforts are needed to address these regions' shortcomings. Based on the results of the PSM-DID model, which controls for selection bias, it is recommended to establish a regional collaboration platform. This platform could enable the eastern region's successful practices to be adapted to the central and western regions, avoiding policy misalignment and ensuring more effective implementation.

Heterogeneity analysis reveals stronger policy effects in eastern China compared to central and western regions, potentially due to technological and financial advantages in the east. However, the selection of pilot cities (e.g., favoring economically developed areas) might exacerbate regional disparities, thereby amplifying the observed policy effects.

4. Conclusion and Prospect

4.1 Research Conclusions

Based on panel data from 284 prefecture-level cities in China from 2004 to 2020, this study uses population size, per capita affluence, industrial structure, energy consumption intensity, energy structure, output value ratio, average employee salary, greening rate of built-up areas, financial deepening degree, fiscal expenditure intensity, R&D investment, and energy structure (power ratio) as control variables. The PSM-DID model was established to analyze the impact of low-carbon city pilot policies on carbon emissions, and a comparison between the DID and PSM-DID models was conducted to highlight the advantages of the selected model. The main findings are as follows: (1) The implementation effect of the LLC in eastern China is significant, effectively curbing carbon emissions. The coefficient for the pilot state variable is negative and passes the significance test, indicating a clear negative relationship between policy implementation and carbon emission reduction. (2) Significant regional differences exist in the factors influencing carbon emissions. The study found that the clean energy structure and per capita wealth had a large impact on carbon emissions in the eastern region, with an obvious promotion effect, while the policy effect in the central and western regions was relatively weak. (3) The implementation batch, scope, and region of the LLC have a significant impact on its effectiveness. The effect of low-carbon city pilot policies is comprehensively influenced by the implementation batch, scope, and region. Cities with early implementation typically achieve significant results faster, while the development levels of different regions and various implementation scopes show significant heterogeneity in the carbon emission reduction effects of low-carbon city pilot policies.

4.2 Policy Recommendations

First, when designing pilot policies for low-carbon cities, regional differences in economic development and energy structures must be fully considered, and policies should be tailored to local conditions. In the eastern region, with its relatively strong economic foundation, the focus should be on developing and utilizing clean energy. Local governments should encourage cities in the east to increase investments in clean energy technologies, promote the adoption of renewable energy, and reduce reliance on traditional fossil fuels. Additionally, governments can encourage businesses and residents to adopt low-carbon technologies and clean energy through financial subsidies, tax incentives, and other measures, fostering a favorable environment for low-carbon development.

Second, based on regional characteristics, it is recommended to implement the LLC gradually, in phases. The policy can begin in cities with a strong economic base and high awareness of low-carbon goals, and later expand to other regions after gaining experience. This approach not only reduces implementation risks but also encourages the low-carbon transformation of surrounding areas through successful case demonstrations. Additionally, the policy promotion should align with the local industrial structure and resource endowments to ensure its adaptability and effectiveness.

Third, establishing a robust policy evaluation mechanism is essential. Local governments should regularly assess the effectiveness of low-carbon city pilot policies, collect and analyze relevant data in a timely manner, and evaluate the actual impact of policies on carbon emissions. Through these evaluations, problems and shortcomings in policy implementation can be identified, enabling prompt adjustments and optimizations to ensure policies remain adaptable to changing economic and environmental conditions. Furthermore, the government should strengthen collaboration with research institutions, universities, and social organizations, leveraging their expertise and technical support to enhance the scientific accuracy of policy evaluations.

Fourth, future research should further examine the impact of low-carbon city pilot policies on other environmental indicators, such as air quality and ecosystem health. Low-carbon policies should not only focus on reducing carbon emissions but also on improving overall environmental quality. Therefore, a multi-dimensional evaluation system should be established to comprehensively assess the relationship between carbon emission reduction and ecological protection during policy implementation. Additionally, the study scope can be expanded to include more cities and regions, and updated data can be used to verify the universality and adaptability of the policy's effects, thereby supporting more comprehensive carbon reduction strategies.

4.3 Research Prospects

First, due to limited data availability, the city-level panel data in this study is incomplete, with some missing data. Additionally, only data before 2020 were collected, which introduces a time lag in the evaluation results.

Second, despite the robustness of the PSM-DID approach in controlling observable confounders, several limitations remain that may lead to biased results. One such limitation is selection bias: the non-random assignment of pilot cities may be influenced by unobserved factors (e.g., local governance efficiency, technological readiness), potentially biasing the policy effect estimates. Additionally, omitted variables such as clean technology investment intensity or environmental regulation enforcement were not included in the model, which could affect the precision of the results. Future research could enhance causal inference by exploring more optimal matching methods, such as the new matching approach proposed by Xie (Shenxiang et al., 2021), and employing more advanced models like triple difference models or machine learning techniques to offer a more comprehensive analysis of the impact of low-carbon policies and uncover potential nonlinear relationships in policy implementation (Chuang et al., 2023). Furthermore, incorporating instrumental variables or granular datasets (e.g., firm-level technology adoption records) could help address these limitations and improve the reliability of findings.

Third, this study focuses only on the effect of low-carbon city pilot policies on carbon emissions, but carbon emission reduction policies also impact other areas, such as pollution reduction, economic structure, and industrial changes (Jing et al., 2023; Qing-feng, 2020; Siyu & Bing, 2023). By including additional explanatory variables, the policy effects could be measured more comprehensively.

Fourth, this study examines the effects of carbon emission reduction policies within a single city, which has certain limitations. Future research could explore the low-carbon transition paths in cities with different levels of economic development and resource endowments through comparative analysis across urban clusters. Furthermore, the implementation of low-carbon city pilot policies may affect neighboring regions, so adjustments should be made in adjacent cities. Establishing a cross-regional coordination mechanism to promote resource sharing and technology transfer will strengthen the overall regional capacity for low-carbon development.

Acknowledgements

This work was supported by the Guangxi Natural Science Foundation (Grant No. 2025GXNSFBA069559) and the Doctoral Research Startup Project of Nanning Normal University (Grant No. 20180406001).

References

Böckerman, P., & Ilmakunnas, P. (2009). Unemployment and self-assessed health: Evidence from panel data. *Health Economics, 18*(2), 161-179. https://doi.org/10.1002/hec.1361

Chengying, L., & Jianping, L. (2022). Policy effects, emission reduction paths, and insights for carbon peak in low-carbon pilot projects: Based on PSM DID test of 275 cities in China. *Journal of Hubei University (Philosophy and Social Science), 49*(6), 159-168. https://doi.org/10.13793/j.cnki.42-1020/c.2022.06.015

Chuang, L., Zhijia, W., & Liping, W. (2023). The impact of carbon emission trading policy on firms' green technology innovation: Based on instrumental variables and triple difference test. *Science of Science and Management of S.& T., 44*(5), 15-33.

Jing, Z., Jun, S., & Meng, X. (2023). Does carbon emission trading promote the transformation and upgrading of industrial structure? Empirical evidence from China's carbon emissions trading pilot policy. *On Economic Problems, 2023*(8), 84-91. https://doi.org/10.16011/j.cnki.jjwt.2023.08.010

Ju, X., Zhao, X., & Sun, B. (2020). Internet and trade costs: An empirical analysis based on cross-border ecommerce data from China SME exports. *Economic Research Journal, 55*(2), 181-196.

Lin, Y., Shen, Y., & Sun, A. (2020). Evaluating the stimulus effect of consumption vouchers in China. *Economic Research Journal, 55*(7), 4-20.

Qi, S., & Jiaqi, L. (2024). The impact of national-level strategic emerging industry clusters on the high-quality development of cities: An empirical study based on PSM-DID. *Modern Management Science, 2024*(1), 44-54.

Qiao, W., & Shuo, S. (2020). Green growth effect assessment of Chinese low-carbon pilot from the perspective of urban heterogeneity. *Soft Science, 34*(9), 1-8. https://doi.org/10.13956/j.ss.1001-8409.2020.09.01

Qilin, M., & Jiayun, X. (2014). Whether the outward foreign direct investment of Chinese enterprises has promoted enterprise innovation or not. *The Journal of World Economy, 37*(8), 98-125. https://doi.org/10.19985/j.cnki.cassjwe.2014.08.006

Qing-feng, C. (2020). Driving effects of national new zone on regional economic growth: Evidence from 70 cities of China. *China Industrial Economics, 2020*(7), 43-60. https://doi.org/10.19581/j.cnki.ciejournal.2020.07.014

Shenxiang, X., Pengfei, F., & Yuanyuan, W. (2021). Improvement and application of classical PSM-DID model. *Statistical Research, 38*(2), 146-160. https://doi.org/10.19343/j.cnki.11-1302/c.2021.02.011

Siyu, Z., & Bing, Y. (2023). Research on the co-benefits of pollution reduction and carbon reduction of "emissions trading" and "carbon emissions trading": Based on the dual perspectives of pollution control and policy management. *Chinese Journal of Environmental Management, 15*(1), 102-109. https://doi.org/10.16868/j.cnki.1674-6252.2023.01.102

Song, Y., Chen, X., Li, Z., Zeng, Z., & Zhang, M. (2022). Exploring the effect of a low-carbon city pilot policies on carbon dioxide emission intensity: Based on the PSM-DID method. *Chinese Journal of Population, Resources and Environment, 20*(3), 209-216. https://doi.org/10.1016/j.cjpre.2022.09.001

Wang, H., Chen, C., Xiong, Z., & Li, D. (2023). How to achieve carbon neutrality in cities? Evidence from China's low-carbon cities development. *International Journal of Environmental Research and Public Health, 20*(3), 2121. https://www.mdpi.com/1660-4601/20/3/2121

Weibing, L., & Kaixia, Z. (2019). The impact of air pollution on firm productivity: Evidence from Chinese industrial firms. *Journal of Management World, 35*(10), 95-112+119. https://doi.org/10.19744/j.cnki.11-1235/f.2019.0134

Xu, A., Song, M., Wu, Y., Luo, Y., Zhu, Y., & Qiu, K. (2024). Effects of new urbanization on China's carbon emissions: A quasi-natural experiment based on the improved PSM-DID model. *Technological Forecasting and Social Change, 200*, 123164. https://doi.org/10.1016/j.techfore.2023.123164

Yang, H., Gan, T., Liang, W., & Liao, X. (2022). Can policies aimed at reducing carbon dioxide emissions help mitigate haze pollution? An empirical analysis of the emissions trading system. *Environment, Development and Sustainability, 24*(2), 1959-1980. https://doi.org/10.1007/s10668-021-01515-9

Yan-ping, Z., Jing, L., & Hui-ying, C. (2024). The impact of clean energy demonstration provincial policies on carbon emissions and economic development in pilot areas: Verification based on multi-phase PSM-DID. *Soft Science, 38*(1), 53-60+82. https://doi.org/10.13956/j.ss.1001-8409.2024.01.08

Yi, L., Zhihui, L., & Zhixiang, G. (2017). Individual tax reform of marriage matching, intergenerational mobility and family pattern. *Journal of Management World, 2017*(9), 60-72. https://doi.org/10.19744/j.cnki.11-1235/f.2017.09.006

Yijun, L., Yanan, W., & Yuan, C. (2023). The impact of the industrial internet on the digital transformation of manufacturing enterprises: Verification based on multi-time point PSM-DID. *Enterprise Economy, 42*(8), 83-92. https://doi.org/10.13529/j.cnki.enterprise.economy.2023.08.008

Ying, M., Mengjie, Q., & Lizhen, Z. (2022). Regional emission reduction effect of carbon emissions trading pilot: Based on PSM-DID model. *Science Technology and Industry, 22*(5), 235-240.

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